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Monitoring the Ocean Acoustic Environment: A Model-Based Detection Approach

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MONITORING THE OCEAN ACOUSTIC ENVIRONMENT: A MODEL-BASED DETECTION APPROACH

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A model-based approach is applied in the development of a processor designed to passively monitor an ocean acoustic environment along with its associated variations. The technique employs an adaptive, model-based processor embedded in a sequential likelihood detection scheme. The trade-off between state-based and innovations-based monitor designs is discussed, conceptually. The underlying theory for the innovations-based design is briefly developed and applied to a simulated data set.

1. INTRODUCTION

In this paper a model-based approach is applied in the development of a processor designed to passively monitor a shallow water, ocean acoustic environment along with its associated variations [1-3]. In order to develop the monitor, we must incorporate our knowledge about the current ocean environment and its changes as time evolves. One way to accomplish this is through models that represent the ocean acoustics coupled with other *a priori* information to provide initial parameters for the processor. The technique employs an adaptive, model-based processor (MBP) embedded in a sequential likelihood detection scheme [4,5].

The ocean acoustic monitor passively "listens" and "learns" whether or not there is a target in the surveillance volume that is being monitored. Our approach is to develop a monitor that first "learns" about its current environment during its initialization phase and then "listens" for *changes from the normal* to declare an anomaly (possibly a target). This concept represents the basic philosophy that will be used to construct our monitors or *model-based detectors*. Once an anomaly or change from the normal is detected, the processor can then proceed to classify the target using a multiple hypothesis scheme and any other target information available.

The trade-off between state-based and innovations-based monitor designs is discussed. The underlying theory for the innovations-based design is briefly discussed and applied to a simulated data set. First, we investigate the underlying processor, conceptually to motivate the subsequent theoretical development and show that there are a number of different approaches that could be employed to solve the basic detection problem. Next, we develop these approaches and show how they can be implemented using the basic MBP.

2. MODEL-BASED DETECTION

Philosophically, the idea that we pursue in this paper is based on the fact that the typical goal of the ocean acoustic monitor will be to passively "listen" and "learn" whether or not there is a target in the surveillance volume that is being monitored. Clearly, developing models of various targets and their particular acoustic signatures is desirable, but may not be practical, or for that matter, even attainable. Therefore, our approach is to develop a monitor that first "learns" about its current environment during its initialization phase and the 'listens" for *changes from the normal* to declare an anomaly (possibly a target).

In order to develop a "change from normal" monitor, we must incorporate our knowledge about the current ocean environment and its changes as time evolves. One way to accomplish this is through propagation, measurement and noise models which represent the ocean acoustics, coupled with other information such as sound speed, temperature, salinity etc. and any historical information available to provide initial parameters for the processor. Once initialized, the processor should then be adaptive, so it can listen and adjust its parameters

(slowly) as the environment changes. *Slowly* is the key, because as a target enters the surveillance volume the processor will not be capable of tracking the rapid acoustic changes created, and therefore the monitor must decide that a *change* has occurred. This concept represents the basic philosophy that will be used to construct the *model-based detectors*.

The basic objective is to design a robust device capable of providing accurate estimates of the current environment and a timely detection of the target disturbing that environment. Suppose we have an *L*-dimensional vertical sensor array and we obtain a set of narrowband pressure-field measurements $\{\mathbf{p}(\underline{z}_\ell)\}$ for $\ell = 1,\cdots,L$, where $\underline{z}_\ell$ represents the sensor spatial coordinates and $\mathbf{p}(\underline{z}_\ell)$ represents the snapshot across the array; thus, we represent the overall measurement process by the model

$$\mathbf{p}(\underline{z}_\ell) = \mathbf{c}[\underline{x}_\ell, \theta_\ell] + \mathbf{v}(\underline{z}_\ell) \, , \tag{1}$$

where $\mathbf{c}[\underline{x}_\ell, \theta_\ell]$ is the nonlinear N_p -measurement vector function made up of the N_x -state vector $\underline{x}_\ell$ (modes, rays, etc.) and unknown N_θ -parameter vector (attenuation, wave numbers, modal coefficients, etc.) with the additive, zero-mean, white N_p -measurement noise vector $\mathbf{v}(\underline{z}_\ell)$ with corresponding covariance, $R_{vv}(\underline{z}_\ell)$ representing the measurement uncertainties and the near-field ambient noise fields. Any changes in the state vector can be used to infer an abnormal environmental condition, which must be further classified as target or not. For instance, if we assume a shallow ocean such that the states are modal functions and that the target disruption causes changes in the gains or modal coefficient parameters from the normal, then it is these changes that can be exploited to perform the detection. These states can be estimated from the noisy pressure-field snapshots using a model-based scheme [4] with an ocean acoustic propagation model embedded within its structure as well as measurement and noise as in Eq. 1. The output of the MBP are enhanced estimates of the states $\hat{\mathbf{x}}_\ell$; parameters, $\hat{\theta}_\ell$; pressure-field, $\hat{\mathbf{p}}(\underline{z}_\ell)$ and the corresponding residuals or *innovations*, $\mathbf{e}(\underline{z}_\ell)$, which is the difference between the measured and predicted pressure-fields, that is,

$$\mathbf{e}(\underline{z}_\ell) = \mathbf{p}(\underline{z}_\ell) - \hat{\mathbf{p}}(\underline{z}_\ell) \tag{2}$$

where $\hat{\mathbf{p}}(\underline{z}_\ell) = \mathbf{c}\left[\hat{\mathbf{x}}_\ell, \underline{\theta}_\ell\right]$ and the corresponding *state* is given by

$$\hat{\mathbf{x}}(\underline{z}_\ell \mid \underline{z}_\ell) = \hat{\mathbf{x}}(\underline{z}_\ell \mid \underline{z}_{\ell-1}) + \mathbf{K}\left[\hat{\mathbf{x}}, \hat{e}\right](\underline{z}_\ell) \tag{3}$$

with $\mathbf{K}$ a weighting (Kalman gain) matrix. Note that the notation $\hat{\mathbf{x}}(\underline{z}_\ell \mid \underline{z}_{\ell-1})$ implies that the state estimate at position $\underline{z}_\ell$ is based on $\underline{z}_{\ell-1}$ previous measurements. Equations 2 and 3 are the primary quantities of concern in the model-based detection schemes. In our modal example, the filtered (corrected) state is an estimate of the modal function at position $\underline{z}_\ell$, while the innovation is the error between the measurement and its prediction at $\underline{z}_\ell$. During normal monitoring, the processor will adaptively track changes in the ocean environment. When the model-based processor is *tuned*, the embedded models "match" the environment, the state estimates (modes, rays, parameters, etc.) are tracking and the resulting innovations are zero-mean and white [4]. Should a target enter the surveillance volume it would disrupt the environment and be reflected in the pressure-field measurement causing the innovations to become non-zero mean and/or non-white.

Various model-based monitoring schemes can be developed using this approach. We restrict them to two basic classes: (1) model the target and its environment (tracking); or (2) model the environment and investigate detectable changes due to model mismatch. Mismatch in the processor is reflected by variations in the innovations statistics, that is, they become biased and correlated. Thus, for the first class, a state-based processor is developed relying entirely on its ability to accurately track the states of interest, while the second approach relies on detecting model mismatch when an anomaly occurs causing a change. We call the tracking detection schemes, *state-based monitors* and the change detection schemes, *innovations-based monitors* (Fig. 1). There exists an inverse relationship between state-based and innovations-based monitors because the former relies on state tracking implying a "tuned" MBP while the latter relies on mismatch and therefore, an "unturned" processor for detection. We illustrate this relationship conceptually in Fig. 2 where we see the state estimate under normal conditions, the presence of a target and then the removal of the target from the surveillance volume. The ideal state-based monitor would not only know the target acoustics (or have an embedded model) but also have some *a priori* knowledge of the target's track much like that of an airplane arriving at an airport where it is identified and tracked. In our case there will be a time lag when the target first enters the volume (as shown in Fig. 2) because the tracker cannot instantaneously follow the target, but it eventually catches up. We show the corresponding innovations for this track and since the tracker is "tuned" the innovations are unbiased and white. For the same scenario we show the innovations-based monitor which is tuned only to the environment. With no target present, we see that the innovations are also zero mean and white, but when the target enters the volume, the innovations become biased since there is no model of the target included and therefore, we see the "jump". After the target exits, the innovations again eventually return to normal. So we see that the inverse relationship between the two distinct approaches. *State-based monitors* are based on tracking the target with the cost of a significant amount of a- priori target information required, while *innovations-based monitors* are based on not tracking and mismatch occurring and the underlying innovations statistics for the detection. Next we briefly discuss, the underlying detection theory for the innovations-based monitor design, since that approach is our primary concern with the lack of target models.

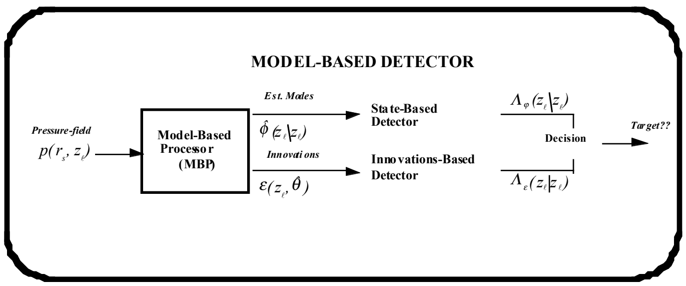

Fig. 1: Model-based detector: MBP, state-based and innovations-based detection schemes.

3. THEORY

In this section we discuss the design of a detector to monitor the performance of the model-based processor and indicate when the model is no longer adequate or does not track the measured data. First, we briefly discuss the required theory. Once this is accomplished, we discuss the development of a practical processor and apply it to our simulated data sets.

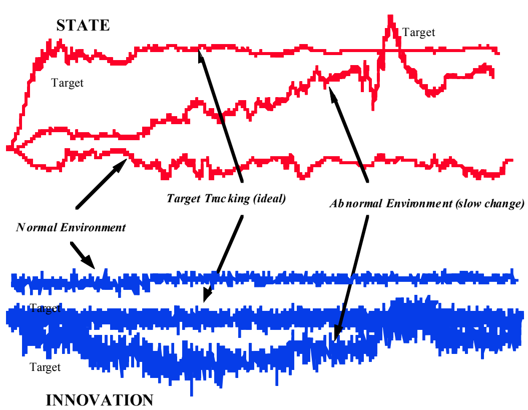

Fig. 2: Conceptual model-based detection showing state-based and innovations-based MBP outputs (monitor inputs) for normal, tracking and abnormal environments.

When we apply the extended Kalman filter (EKF) to measured array data, we not only reconstruct the modal/range functions and pressure-field measurements, but also provide a whitening operation transforming the correlated measurements to the uncorrelated innovations sequence, $e(\underline{z}_\ell)$ [6]. It is well known that a necessary and sufficient condition for a Kalman filter to provide optimal performance is that the innovation sequence is zero-mean and white. Thus, the innovations sequence is zero-mean and white only when the propagation and measurement models reflect the true ocean acoustics and noise and the EKF is properly tuned. Statistical changes in $e(\underline{z}_\ell)$ reflect changes from the normal or expected operation; therefore, we can utilize these changes to monitor the performance of the propagation model employed in the processor. First, we develop the theoretical monitor. From the insight we gain in its development, we then investigate a more pragmatic approach and apply it to our shallow water problem.

Theoretically, it can be shown that when "model mismatch" occurs, the innovations become non-zero mean and are no longer white; therefore, we must develop a monitor that decides whether or not the innovations satisfy the required properties, that is, we test the hypothesis that

$$\begin{aligned} H_o &: \quad \{\mathbf{e}(\underline{z}_\ell)\} \sim N(\mathbf{0}, \mathbf{R}_{\mathbf{ee}}(\ell)) \\ H_1 &: \quad \{\mathbf{e}(\underline{z}_\ell)\} \sim N(\overline{\mu}_e(\underline{z}_\ell), \overline{\mathbf{R}}_{\mathbf{ee}}(\ell)) \end{aligned} \tag{4}$$

which is a statistical test for the zero-mean and whiteness of the innovations sequence. Note that we assume that we *know* the model error and how to calculate $\overline{\mu}_e, \overline{\mathbf{R}}_{ee}$ *a priori*. The optimal solution to this problem is based on constructing the likelihood ratio for the *sequential innovations detector* (SID) with assumed gaussian distributions [6] to obtain the decision function

$$\lambda(z_{\ell+1}) = \lambda(z_\ell) + \frac{1}{2}\mathbf{e}'(z_\ell)\mathbf{R}_{\mathbf{ee}}^{-1}(z_\ell)\mathbf{e}(z_\ell) - \frac{1}{2}\left(\mathbf{e}(z_\ell) - \overline{\mu}_e(z_\ell)\right)'\overline{\mathbf{R}}_{\mathbf{ee}}^{-1}(z_\ell)\left(\mathbf{e}(z_\ell) - \overline{\mu}_e(z_\ell)\right) \tag{5}$$

which is compared to a threshold. The implementation of this monitor presents some basic problems, but does illustrate a potential optimal solution to the model monitoring problem. As mentioned, the SID requires *a priori* knowledge of the actual model "mismatch" and structurally how it enters the propagation model to obtain [$\overline{\mu}_e, \overline{\mathbf{R}}_{ee}$] for the monitor.

Next we consider the development a more practical statistical test for model mismatch, the *weighted sum squared residual* (WSSR) test [6]. The WSSR statistic essentially aggregates all of the information available in the innovation vector over some finite window of N samples. It is defined by

$$\rho(k) \ldots \sum_{k=\ell-N+1}^{\ell} \mathbf{e}'(z_\ell)\mathbf{R}_{\mathbf{ee}}^{-1}(z_\ell)\mathbf{e}(z_\ell) \qquad \ell \; ? \; N \tag{6}$$

which is compared against a threshold. In this case H_o is the hypothesis that there is no model "mismatch" (white innovations), while H_1 is the hypothesis that there is mismatch specified by non zero-mean, non-white innovations.

4. SIMULATION RESULTS

In this section we briefly discuss the results of execution the WSSR detector on simulated shallow water data. We assume a flat bottom, a range independent three layer shallow ocean environment with a depth of 100m, a sediment depth of 2.5m, and a subbottom. A vertical line array of 100 sensors spaced at 1m spans the entire water column and a narrowband (100 Hz) source is located at a depth of 50 and a range of 0.5 Km. Our *normal* ocean environment is modeled by a far away source at 20Km synthesizing ambient noise at the array. The parameters for the run were generated by the SACLANT normal-mode simulator SNAP and the can be found in Ref. [4]. We show the results of the whiteness and WSSR run for the normal and abnormal ocean. Here we tuned (zero mean, white innovations) the processor to the ambient ocean and then "listened" for changes. The results are shown in Fig. 3 below. In Fig. 3a, we see the whiteness test indicating the zero-mean/white innovations with the WSSR statistic lying below the threshold, while the results when a target approaches the array at 0.5 Km clearly indicate a non-zero mean, non-white process with the WSSR exceeding the threshold illustrating the point.

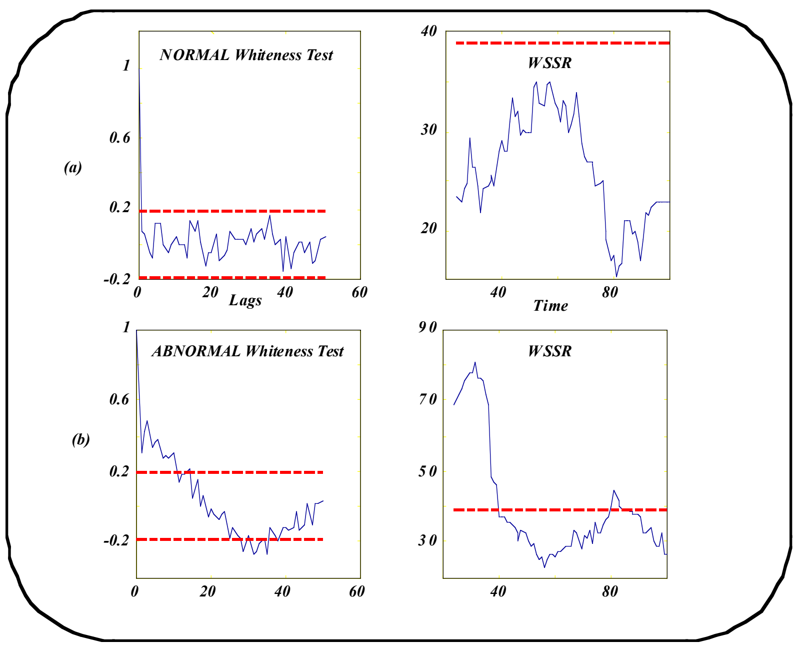

Fig. 3: Normal/Abnormal SNAP Simulations: (a) Normal case: Zero-Mean/White (1.5e-8<4.6e-8/0%) and WSSR below threshold. (b) Abnormal case: Zero-Mean/White (4.6e-8<5.9e-8/0%) and WSSR exceeds threshold.

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